Project ID# eems062
Pillar(s): CAVs

Deep-Learning for Automated Vehicle (AV) Development

Robert M. Patton

Oak Ridge National Laboratory

2019 Vehicle Technologies Office Annual Merit Review

June 12, 2019

Overview

Timeline

- Project start: October 1, 2018
- Project end: September 30, 2021
- Percent complete: 20%

Budget

- Total project funding
  - DOE share: 100%
  - Contractor share: 0%
- Funding received in FY 2018
  - $ 1.0M
- Funding received in FY 2019
  - $ 1.9M

Barriers

- Proprietary or expensive simulation tools and imagery for development of autonomous vehicle algorithms
- Significant expertise and manual effort required to develop machine learning algorithms
- Machine learning algorithms developed using desktop computing power

Partners

- Lead: Oak Ridge National Laboratory (ORNL)
- National Renewable Energy Laboratory (NREL)

Relevance

- Challenges
  - Much research in machine learning for CAVs is heavily focused on sensing / perception, and is often isolated from other aspects such as control or communication
  - Machine learning for CAV operation was initially heavily focused on safely operating according to traffic control structures first formed in the early 1900s with little to no concern for energy efficiency
  - Further exploration of machine learning for energy efficient CAV operation is needed

- Objective
  - Demonstrate HPC-based ability to analyze large data sets from prototype self-driving vehicles and discover higher performance and resilient operating algorithms for sensing, perceiving, and control.
  - Develop and demonstrate new machine learning based algorithms for vehicle operating controls that are capable of scaling to "Level 5" autonomous vehicle capabilities.
  - Develop a virtual test environment capable of training & safely evaluating autonomous vehicle operating controls over millions of miles and scenarios/environments expected to be encountered

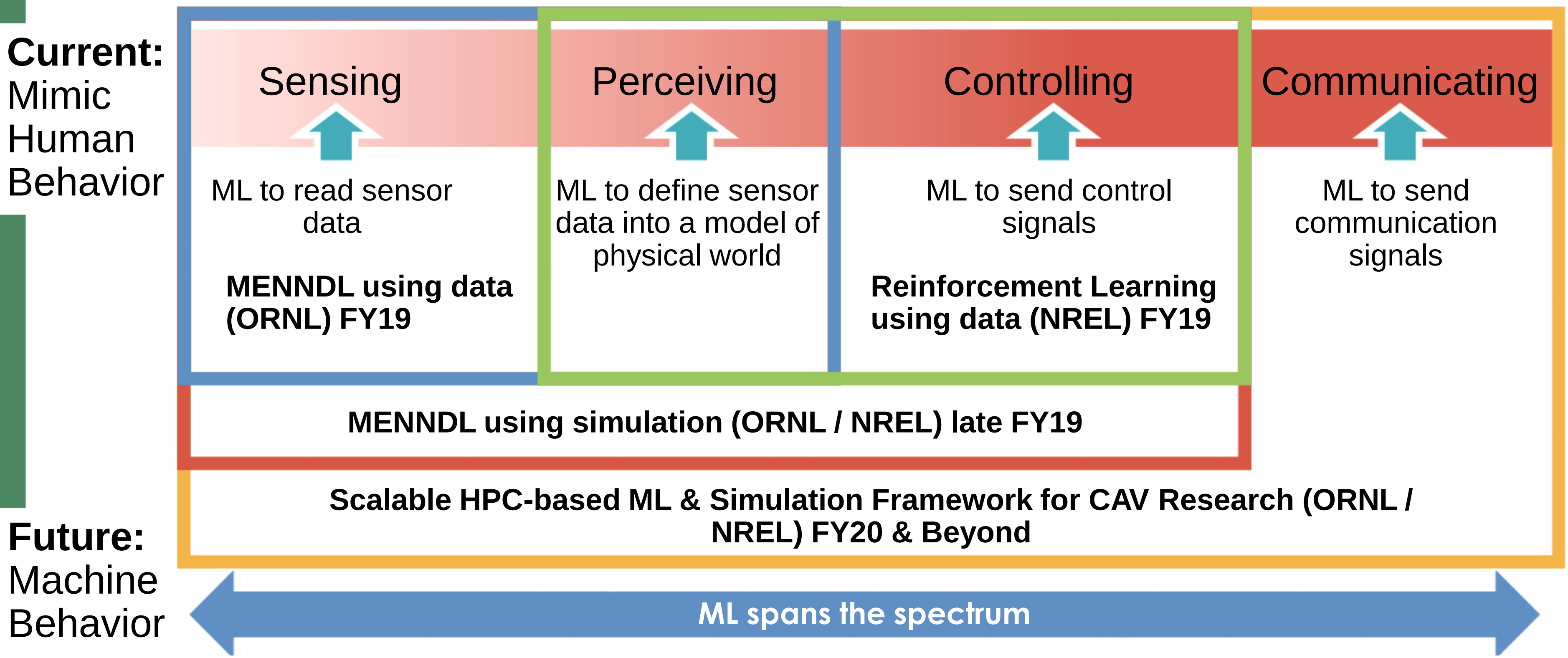
Milestones

Milestones	FY19 Q1	FY19 Q2	FY19 Q3	FY19 Q4
1. Evaluate driving simulators to be used for training deep learning networks to perform control for CAVs				
2. Generate data using selected driving simulator to create data set for training neural networks to perform control for CAVs				
3. Develop new approach for training machine learning algorithms in a virtual environment				
4. Summary report				

Any proposed future work is subject to change based on funding levels

Approach (1)

Connected Autonomous Vehicles



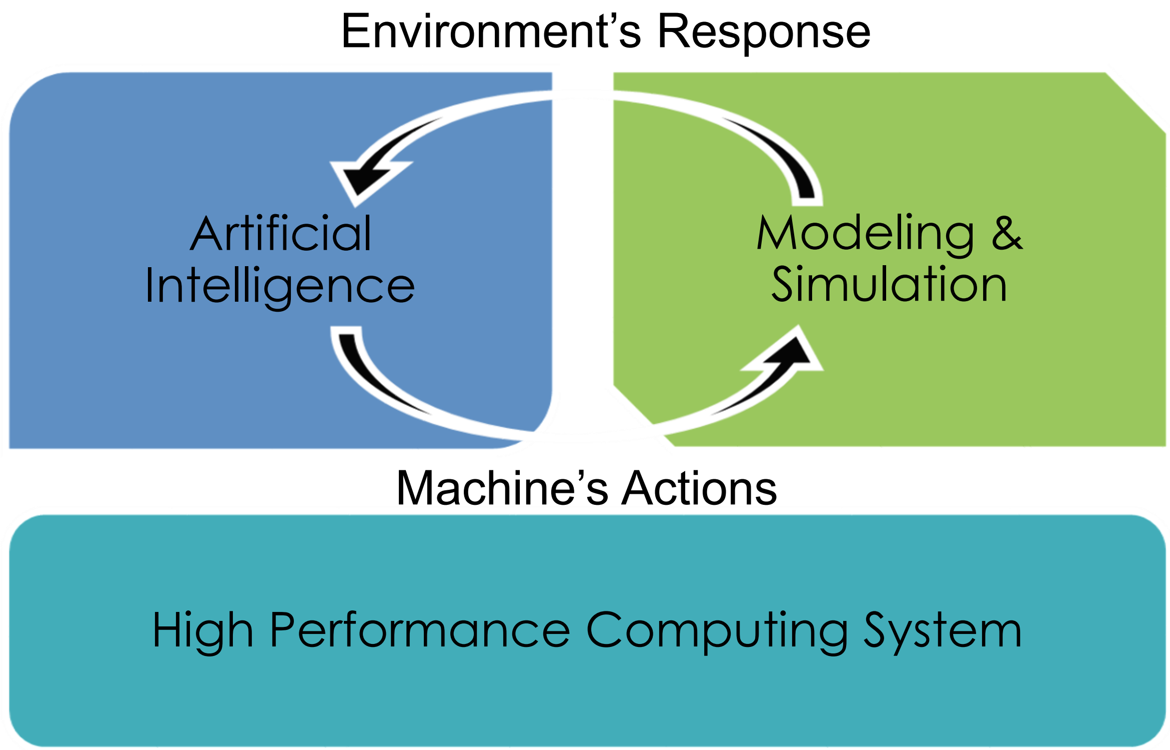
Goal

Develop a computational capability that leverages **Modeling & Simulation, High Performance Computing, and Artificial Intelligence** in order to enable the rapid development of perception, control, and communication algorithms for CAV

Approach (2)

End Goal

Develop a computational capability that leverages
Modeling & Simulation
High Performance Computing
Artificial Intelligence
in order to enable the rapid development of perception, control, and communication algorithms for CAV



Starting small in each area, and scaling larger over time

- FY19 Milestones and Deliverables lead to a small scale version of the End Goal
- FY20 and Beyond brings scalability and enhancements to the End Goal

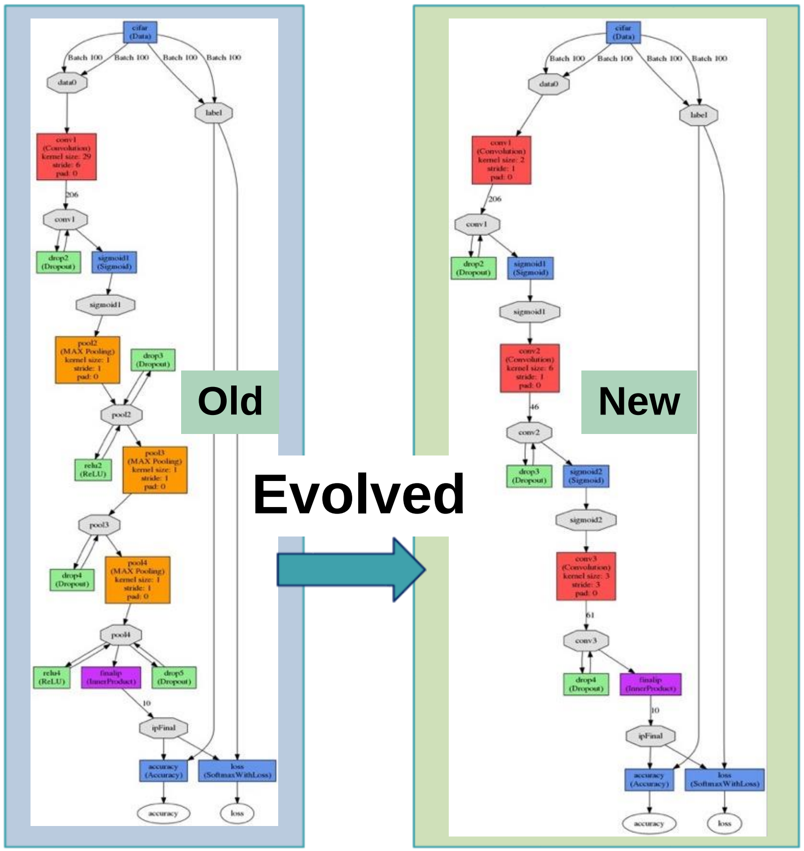
Technical Accomplishments

Technical Accomplishments and Progress -Summary

1. Developed new automated approach to creating multi-stack neural network architectures for AV perception (slide 10)
2. Developed new approach to generating data for imitation learning that does not require human interaction (slide 11)
3. Evaluated scenario generation capability (slide 12)
4. Evaluated existing neural networks for perception (slide 13 & 14)
5. Ongoing:
   - Generating data for Imitation Learning
   - Developing interface to support Reinforcement Learning development with driving simulator

MENNDL

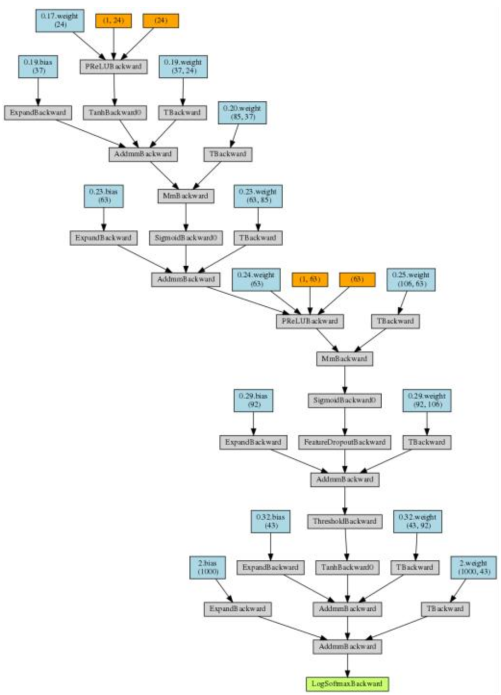
Multinode Evolutionary Neural Networks for Deep Learning



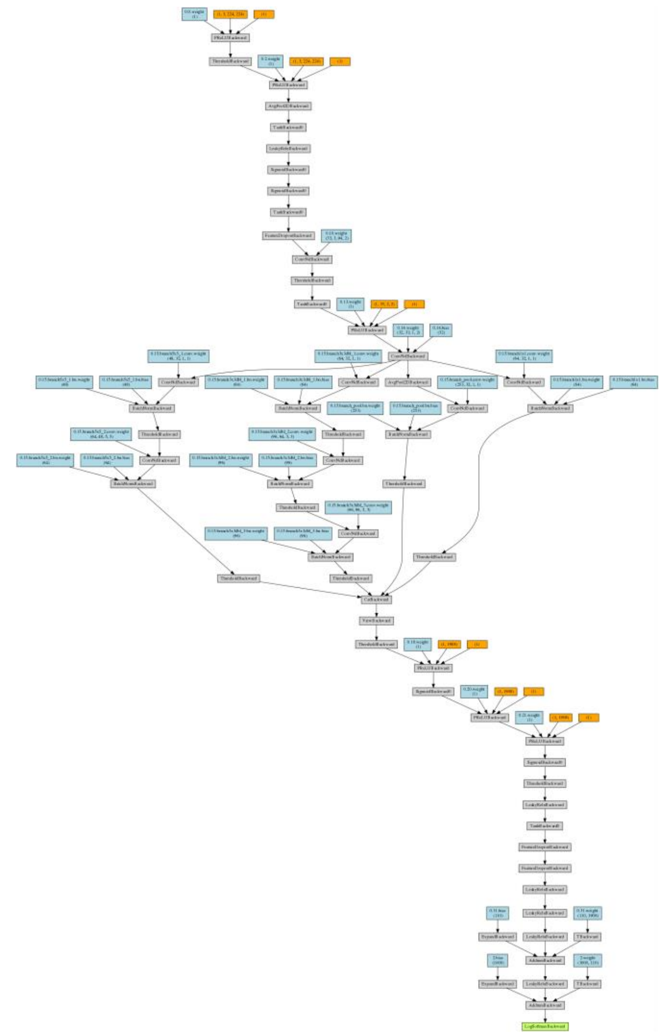
- Deep Learning (DL) must be tailored to an application, which can require months of manual effort with a significant amount of expertise
- Inspired by Gregor Mendel's pea plant experiments, MENNDL automatically breeds DL networks that best suit an application
- MENNDL works by evolving a population of deep learning neural networks
- MENNDL creates networks that typically go beyond what a human expert would have thought to try, and does this within hours
- **DL network tailored to an application within hours and with very little expertise**
- 2018 Gordon Bell Award Finalist
- 2018 R&D 100 Award Winner
- Scaled to +4,000 nodes / 27,000 GPUs of Summit and 152.5 PFlops measured, 167 PFlops projected

MENNDL for Perception

Deep neural networks for perception in autonomous vehicles requires more complex network structures than for other compute vision tasks

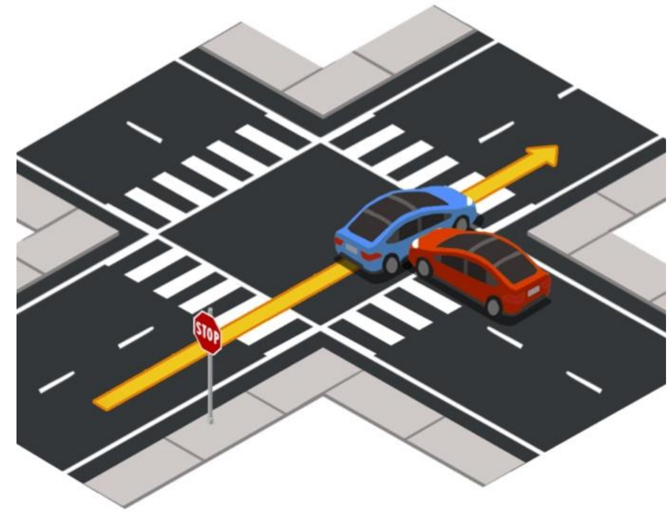


Evolving Deep Neural Networks for KITTI Dataset



Training Data to Support Imitation Learning

- Currently, using CARLA, which is an open-source simulator for autonomous driving research (http://carla.org/)
- Step 1 (done): Leveraging CARLA's Autopilot & Roaming Agent to generate data from cameras, controls, interaction
- Step 2 (**current**): Generate thousands of Autopilot & Roaming Agent runs to create a training data set
  - Could be a publicly releasable data set for CAV community (i.e., resource like ImageNet for computer vision community)
  - May use HPC or large compute resources for this
- Step 3: Utilize MENNDL to create a neural network trained on generated data from Step 2
  - Create our own "autopilot" that performs similarly but doesn't rely on information provided by simulation engine



Automated Scenario Generation

- "Driving" in Carla: We have full access to data for infrastructure and other vehicles. Enables exploration of hierarchy of learning approaches

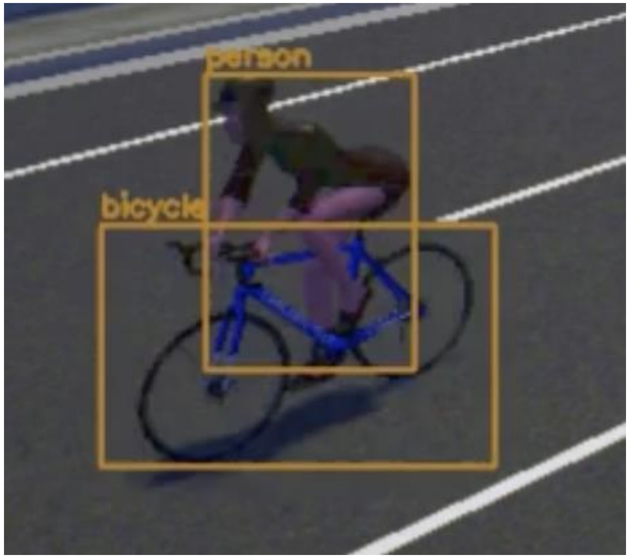
Real Data to Simulation Data

- You-Only-Look-Once (YOLO) deep neural network was trained on real images, then applied to images from CARLA simulator
- First steps toward interchanging real data with simulation and vice versa

Real Data to Simulation Data

- Results below show a perception algorithm trained on real data an applied to simulated data
- Can improvements be made to perception algorithm with simulation data and then applied real data successfully?
- How does the machine behave when information changes from perception?

At a distance



Up close

OAK RIDGE National Laboratory

Responses to Previous Years Reviewers Comments

- Project was not reviewed last year as it is in its first year

REMAINING CHALLENGES AND BARRIERS

- Existing software codes currently built with “desktop” compute power in mind
- Machine learning algorithms require significantly more compute time than anticipated
- CARLA development controlled by outside entities & actively being developed with new features and bugs being released very quickly

PROPOSED FUTURE RESEARCH

- **Scalability:**
  - How large of a simulated driving environment be achieved (e.g., number of cars)?
  - How many different scenarios (*not* miles driven!) can be achieved?
  - How many different driving algorithms can be evaluated?
- **Interoperability:**
  - How to train machine to drive with human drivers?
  - How to train machines to drive with each other?
  - How to train machines to drive with the infrastructure?
- **Trainability:**
  - How to reduce time to solution for training?
  - How to reduce volume of training data or simulation time?
  - How should machines be trained to drive for multi-objectives (e.g., efficiency vs time)?
- **Desired Machine Behaviors:**
  - How do machines drive for increased energy efficiency?
  - How do machines drive in emergency situations (e.g., ambulance mode)?
  - How do machines drive in severe weather conditions (e.g., blizzard, high winds)?

Any proposed future work is subject to change based on funding levels

SUMMARY SLIDE

- **Approach:**
  - Develop a computational capability that leverages Modeling & Simulation, High Performance Computing, and Artificial Intelligence in order to enable the rapid development of perception, control, and communication algorithms for CAV
- **Technical Accomplishments:**
  - Developed new approach to creating multi-stack neural network architectures for AV perception
  - Developed new approach to generating data for imitation learning that doesn't require human effort
  - Evaluated High Res Physics / Low Res Imagery simulations
  - Evaluated scenario generation capability
  - Evaluated existing neural networks for perception using simulation
- **Future Work:**
  - Generating data for Imitation Learning & designing neural network with that data
  - Developing interface to support Reinforcement Learning development with driving simulator
  - Scaling up the computing resources and scenario generation

QUESTIONS?